Evaluation of Texton Spatial Dependence Matrices for Breast Density Classification

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Abstract

Breast density has been shown to be one of the most significant risks for developing breast cancer. The Breast Imaging Reporting and Data System (BI-RADS) has a four category classification scheme that describes the different breast densities. Yet, there is great inter- and intra- observer variability for density classification. This work presents a novel texture classification method and its application for the development of a completely automated breast density classification system. Textons can be thought of as the building block of texture. A new algorithm is proposed that captures the mammographic appearance of the different density patterns by evaluating the texton spatial dependence matrix (TDSM) for the breast region's corresponding texton map. The TSDM is a new texture model that captures both statistical and structural/spatial texture characteristics. The TSDMs are evaluated for different density classes and corresponding texture models are established. Classification is achieved using a chi-square distance measure. The fully automated TSDM breast density classification method is quantitatively evaluated on the Oxford Mammogram Database. The incorporation of texton spatial dependencies allows for classification accuracy reaching over 82%.

1 Introduction

Breast cancer will affect between 1 to 8 women during their lifetime. Breast density has been shown to be one of the main risks for developing breast cancer and this has been confirmed in a number of studies [5], [2]. Breast parenchymal density refers to the prevalence of fibroglandular tissue in the breast as it appears on a mammogram. Additionally, breast density may lower the sensitivity of mammography and obscure lesions. Thus, breast density and change thereof may be used for risk assessment, for reducing screening intervals, but most importantly for signaling the necessity for a more thorough interpretation of certain mammograms for achieving the earliest possible diagnosis.

The American College of Radiology (ACR) [1] proposes the following breast composition classification scheme in the Breast Imaging Reporting and Data System (BI-RADS): (i) the breast is almost entirely fat, (ii) there are scattered fibroglandular densities, (iii) the

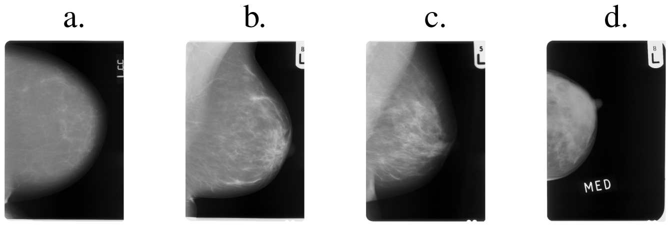

Figure 1: Examples of mammograms from the 4 BI-RADS categories: a) BI-RADS I, b) BI-RADS II, c)BI-RADS III, d) BI-RADS IV.

breast is heterogeneously dense which may lower the sensitivity of mammography and (iv) the breast tissue is extremely dense, which could obscure a lesion in mammography. Mammograms corresponding to the four BI-RADS classes can be seen in Figure 1. Due to the importance of breast density and corresponding changes, radiologists are required to report the breast density for each mammogram. Reporting of breast density suffers from high inter- and intra- observer variability [12]. Automated breast density classification algorithms can overcome this difficulty and provide objective classification of breast density.

A number of techniques have been proposed for breast density pattern classification. Boyd et al. [2] proposed a semi-automatic computer measure based on interactive thresholding and the percentage of the segmented dense tissue over the segmented breast area. Other methods include automatic segmentation based on variance histogram discriminant analysis classification [8], and density classification using a large set of statistical and compositional features in term of BI-RADS [3]. Petroudi et al. [10] proposed a scheme that uses texture models to capture the mammographic appearance within the breast area: parenchymal density patterns are modelled as statistical distributions of clustered, rotationally invariant filter responses i.e. textons [6], in a low dimensional space.

The purpose of this paper is the development of a fully automatic, and highly accurate breast density category classifier based on objective and quantitative texture measures. The presented algorithm builds on the same definition of textons as clustered filter responses [6]. However, instead of using histograms for modeling the different texture classes [10], a new texture descriptor that evaluates the spatial dependence between the textons characterizing the image is introduced and used.

2 Method

The gray-level spatial dependence or co-occurrence matrices (GLCM) measure the frequency of intensity pairs in the gray-level image of neighboring pixels at different distances and directions [4]. Haralick et al. [4] evaluated second order statistics on the corresponding GLCMs for further texture description. However, simple intensity information does not provide adequate information especially for analysis and characterization of many medical images. Thus, following the definition of GLCM presented in [4], a new texture descriptor that captures both structural and statistical texture information is defined, the texton spatial dependence matrix (TSDM), or texton co-occurrence matrix. The term texton co-occurrence matrix was first used by Liu *et al.* in [7]. However, they define textons as different shape descriptors. They define a 2x2 grid, and if three or four of the corresponding pixel values are the same, then those pixels are set to form a texton. If a pixel belongs to a texton the pixel will keep the intensity value of the image where the five texton shapes are evaluated on. The resulting image is what Liu et al. [7] call a texton map. Thus in [7] the corresponding texton map for the intensity image is the same image with the same intensity values, except where the pixels do not match a texton shape and are set to zero. For the TSDM texture descriptor presented here, textons are defined under the operational definition of Leung and Malik [6], resulting in a very different texton map - where each texton corresponds to a vector and not to a pixel intensity value, or a gradient thereof, as in [7].

Let the image to be analyzed defined as I and let $L_x = \{1,2,...,N_x\}$ and $L_y = \{1,2,...,N_y\}$ the spatial domains in X and Y with N_x number of columns and N_y the number of rows. Let TI be the texton map matrix where each entry identifies the texton - under the operational definition of Leung and Malik [6] as clustered filter response -, $T \in \{t_1,2,...,t_n\}$, each pixel is mapped to, as in [10]. There are n textons in the corresponding texton dictionary. TI can be defined as a function that assigns some texton T to each pixel: $TI : L_x \times L_y \rightarrow T$, using a distance measure. Again as in [4], the developed texture measures are angular texton nearest-neighbor spatial dependence matrices (TSDMs) specified by the matrix of relative frequencies P_{t_i,t_j} with which two neighboring pixels mapped to textons t_i and t_j separated by distance d occur on the image's texton map TI. The TSDM for displacement $d = (d_x,d_y)$ can be represented by:

$$TSDM(t_i,t_j,d_x,d_y) = \frac{1}{\sharp} \sum_{k=1}^{N_x} \sum_{l=1}^{N_y} \begin{cases} 1 & if \;\; TI(k,l) = t_i \;\; and \;\; TI(k+d_x,l+d_y) = t_j \\ 0 & otherwise \end{cases} \tag{1}$$

where $\sharp$ defines the total number of elements in the corresponding set. By including a displacement vector in the horizontal and vertical direction the angular relationship between neighboring pixels is inherently incorporated.

For the development of the new TSDM based density classification model the following steps need to take place. Initially the texton dictionary must be derived. Following, segmentation of the breast region [9] the resulting images from the training set are filtered using the Maximum Response 8 (MR8) filter bank proposed by Varma and Zisserman [11]. The texton dictionary is created by clustering the filter responses aggregated over all images per BI-RADS class using the k-means algorithm.

Given the texton dictionary, each image pixel in the breast region of each mammogram in the training set is mapped to the texton closest to it in the filter response space. This step provides the TI image's texton map. TI is then used to evaluate the TSDM for different displacements as shown in equation (1). TSDM matrices for different displacements are computed for each training mammograms. The sets of the TSDMs define the breast parenchymal density models.

To achieve classification, the same steps as above are followed for a test mammogram - segmentation, filtering, evaluation of the corresponding TI and TDSMs. The resulting TSDMs are compared to the TSDMs of all learnt models and the mammograms is assigned to the BI-RADS class closest to it using χ^2 significance test in conjunction with a nearest neighbor rule. For the developed method 10 cluster centers per BI-RADS class are used for the creation of the texton dictionary, and for this paper only the TSDM with $d = 1$ is investigated.

Table 1: Classification accuracy results.

Accuracy%	BI-RADS I	BI-RADS II	BI-RADS III	BI-RADS IV
4 Density Classes	90%	90%	80%	70%

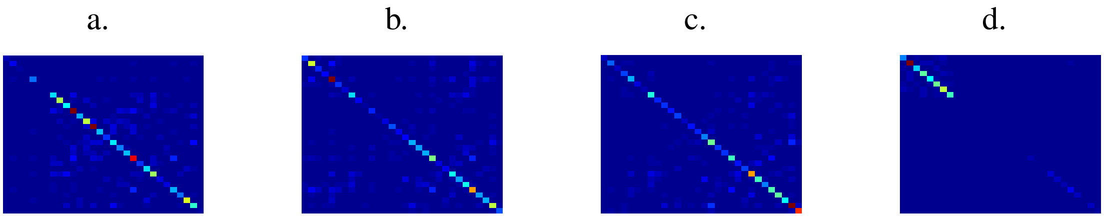

Figure 2: Examples of the TSDMs with distance 1 for the mammograms from the 4 BI-RADS categories shown in Figure 1: a) BI-RADS I, b) BI-RADS II, c)BI-RADS III, d) BI-RADS IV.

3 Results

The algorithm is evaluated on a set of 80 mammogram cases from the Oxford Database [10], 20 from each BI-RADS class for which there was independent agreement in density classification by three expert breast radiologists. 10 mammograms from each class were used for training and 10 for testing. The images correspond to 8-bit mammograms downsampled to 300μm/pixel. Despite the small size of the training set, exact agreement with the ground truth was achieved in 82.5% of the cases. Using simple texton histograms as different mammogram density models results in an accuracy of only 76% [10]. The improvement is expected as the presented method captures additional information regarding the spatial distribution of textons in the breast region.

Table 1 shows the classification accuracy of the presented technique discriminating between the 4 BI-RADS categories based on the ground truth. Accuracy is calculated as the percentage of correctly classified mammograms in a breast parenchymal density category over the ground truth total number of mammograms in that category.

4 Discussion

This paper proposes a new effective texture descriptor that captures both structural and statistical properties. The paper introduces TSDM, which evaluates the relative frequencies with which neighboring pixels are mapped to textons in the texton dictionary. Evaluation of different distance TSDMs and calculation of different texture features from the corresponding matrices will allow for even better texture characterization and improved performance and consistency and will be the subject of future research.

The texture descriptor is incorporated in a method for breast density classification.The results are very good and the TSDMs for the different density classes show good separation between them. Fig. 2 shows the TSDMs for the four mammograms corresponding to the four BI-RADS classes in Fig. 1.

5 Conclusion

A breast density classification approach is presented based on the development of a new texture model TSDM that captures both structural and statistical texture information and builds on the definitions of textons in [6] and spatial dependence matrices in [4]. The presented method defines texture classes as TSDMs over texton [6] dictionaries developed from a training set. Classification is simply a matter of comparing the texton spatial dependence relative frequency matrices using appropriate distance measures. In the future, texture features on TSDMs corresponding to different distances will also be investigated.

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